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A Comparative of Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) Methods for Forecasting Population Density in Iraq from 2024 to 2030

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Abstract: Time series forecasting, a statistical method, involves analysing past data patterns to predict future values. Widely applied in various fields. This research conducts a comparative of Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) methods to forecast population density in Iraq from 2024 to 2030. The study aims to evaluate the accuracy and effectiveness of these forecasting techniques during this period. The data spans from 2000 to 2023, comprising 24 time periods and was obtained from the "Earthly Data-Iraq population density" website. Both SES and DES methods were applied, including variants by Brown and Holt. Tools like Stratigraphic, Minitab, SPSS, and Excel were utilized for forecasting. Mean Absolute Percentage Error (MAPE) was used to assess model performance. Parameter optimization was carried out, revealing that for SES, the optimal α value was 0.99 with a MAPE of 2.61394. For DES Brown's, the optimal α was 0.99 with a MAPE of 0.817392, while for DES Holt's, the optimal α was 0.99 and the optimal β was 0.99, with a MAPE of 0.55047. DES Holt's was identified as the most effective method due to its lowest MAPE compared to other methods.

Keywords: Single Exponential Smoothing, Double Exponential Smoothing, Population Density.

مقارن لطرق التمهيد الأسي المفرد (SES) والتمهيد الأسي المزدوج (DES) للتنبؤ بالكثافة السكانية في العراق من ٢٠٢٤ إلى ٢٠٣٠

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المستخلص: توقع السلاسل الزمنية، وهي طريقة إحصائية، يتضمن تحليل أنماط البيانات السابقة لتوقع القيم المستقبلية. يُطبق على نطاق واسع في مجالات متعددة. يقوم هذا البحث تقارن بين نموذجي التجانس الأسي المفرد

(SES) و التجانسي الأسي المزدوج(DES) للتنبؤ بالكثافة السكانية في العراق من عام ٢٠٢٤ إلى عام ٢٠٣٠. و تقيم دقتها باستخدام البيانات من عام ٢٠٠٠ إلى عام ٢٠٢٣، مشتملة على ٢٤ فترة زمنية وتم الحصول عليها من موقع "بيانات الأرض - كثافة سكان العراق". تم تطبيق طرق SES وDES، بما في ذلك الأشكال البديلة من قبل براون وهولت. وتناقش الأدوات المستخدمة للتنبؤ Stratigraphic و Minitab و SPSS و Excel للتوقع. تم استخدام الخطأ المطلق المتوسط النسبي (MAPE) لتقييم أداء النموذج. تم إجراء تحسين للمعلمات، كشف عن أنه بالنسبة لـ SES، كانت قيمة α الأمثل ٠,٩٩ بـ MAPE قدره ٢,٦١٣٩٤. بالنسبة لـ DES براون، كانت قيمة α الأمثل ٠,٩٩ بـ MAPE قدره ٠,٨١٧٣٩٢، بينما كانت لـ DES هولت قيمة α الأمثل ٠,٩٩ وقيمة β الأمثل ٠,٩٩، بـ MAPE قدره ٠,٠٥٥٠٤٧. تم التعرف على DES هولت كالأكثر فعالية بسبب MAPE الأقل مقارنة بالطرق الأخرى.

الكلمات المفتاحية: التجانس الأسي المفرد، التجانس الأسي المزدوج، الكثافة السكانية.

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1. Introduction [1][2][4]

Population density is a crucial demographic measure, representing the number of individuals per unit area within a specific geographical region. It serves as a vital indicator for understanding the distribution of people and resources in both urban and rural areas. High population densities are often associated with urbanization, leading to increased demands on infrastructure, housing, and natural resources. Conversely, low population densities may signify rural or sparsely populated regions, impacting access to services and economic growth. The understanding of population density is essential for policymakers, urban planners, and researchers to address various challenges, including sustainable development, transportation planning, and disaster management. Accurate measurement and analysis of population density support informed decision-making and effective resource allocation strategies. In Iraq, population density varies across different regions due to factors such as urbanization, geography, and historical settlement patterns. As one of the most populous countries in the Middle East, Iraq experiences significant variations in population density influenced by historical, economic, and geopolitical factors. Understanding population density in Iraq is crucial for addressing socio-economic issues like infrastructure development, resource allocation, and the provision of social services. This overview highlights the importance of population density in shaping Iraq's development trajectory and guiding policy interventions.[6][7][14]

2. Objective of the Research

The research addresses the theoretical and scientific aspects through a comparison of two commonly used methods for time series forecasting, Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) methods, in the context of predicting population density in Iraq. The study applied these methods to real data, integrating theoretical concepts with practical application to scientifically evaluate the effectiveness of different forecasting techniques. Performance evaluation was conducted using statistical measures such as MAPE, without considering other statistical measures to assess performance, and parameter optimization was performed to enhance prediction accuracy.

3. Methods

Data classification methods are extensively employed in statistical techniques. Forecasting, as a predictive tool, utilizes pertinent data, whether historical or current, to anticipate future values. Two primary methods are used: qualitative, which is applied intuitively in the absence of historical data, and quantitative, which relies on mathematical calculations using past data. In this study, Population Density in Iraq was analysed using time series data ranging from 2000 to 2023, sourced from the website (Earthly data-Iraq population density)
.(https://database.earth/population/iraq/density).

The study utilized Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) models for forecasting Population Density in Iraq from 2024 to 2030.[16]

A. Exponential Smoothing Model [8][9][18]

Exponential smoothing, a forecasting technique, involves a continuous calculation process that incorporates the most recent data points. Each data point is assigned a weight represented by the parameter "alpha." The ability to select different values for alpha allows for minimizing prediction errors. The smoothing constant (α) typically falls within the range of 0 to 1, exclusive (0 < α < 1). Exponential smoothing encompasses three main variations: single exponential smoothing, double exponential smoothing, and triple exponential smoothing

(1) The Single Exponential Smoothing (SES) Method [3][17][19]

Single exponential smoothing, also referred to as simple exponential smoothing, is a commonly employed method for short-term forecasting. Praised for its simplicity, it demands minimal computational resources. The model operates with a single smoothing parameter, typically represented as α, which dictates the weight assigned to the most recent observation. This approach is appropriate for data demonstrating primarily horizontal patterns, where cyclic variations or clear trends are absent. Essentially, it assumes that the data fluctuates around a constant mean without exhibiting consistent growth trends or identifiable patterns. The equation for single exponential smoothed statistics is outlined below:

$$F_{t+1} = \propto X_t + (1 + \propto) F_t \qquad (1)$$

The symbol F_{t+1} represents the forecasted value at the time period (t+1), while $X_t + (1+\propto)$ signifies the actual value of the time series at that time. $F_t$denotes the forecasted value at time t. The symbol $\propto$ represents constants whose values lie within the range of 0 and 1.

(2) Parameter Optimization of Single Exponential Smoothing [13][20]

The parameter optimization process employed the golden section method with the goal of minimizing the Mean Absolute Percentage Error (MAPE). This error was calculated by comparing the forecast produced by the Single Exponential Smoothing model with the actual values. The optimization of the Single Exponential Smoothing's parameter (α) was conducted using the golden section technique.

B. Double Exponential Smoothing (DES) Model [10][12][15]

The Double Exponential Smoothing technique, initially introduced by Charles C. Holt and also referred to as Holt's method, marks a significant advancement in time series forecasting. This method, renowned for its effectiveness, serves as a robust tool in forecasting time series data. Unlike simple exponential smoothing, which may struggle with datasets exhibiting a trend, the Double Exponential Smoothing (DES) model adeptly captures both trend and seasonality, thereby enhancing predictive accuracy. To address the limitations of simple exponential smoothing in the presence of trended data, various methods were developed, collectively termed "double exponential smoothing" or "second-order exponential smoothing." This approach involves the recursive application of an exponential filter twice, thus earning the name "double exponential smoothing."

The Double Exponential Smoothing (DES) method, an extension of Simple Exponential Smoothing (SES), introduces additional parameters to improve its ability to capture both the level and trend components present in time series data. These parameters play a crucial role in determining the adaptability and responsiveness of the forecasting model. Key parameters of the Double Exponential Smoothing method include:

The smoothing parameter for level (α), falling within the range of 0 to 1, dictates the degree of influence assigned to the latest observation when updating the level component. A higher α places more emphasis on recent levels, thereby ensuring the model's responsiveness to short-term fluctuations. In DES, the smoothing parameter for trend (β), also ranging from 0 to 1, governs the weight assigned to the most recent trend observation. A higher β prioritizes recent trend changes, facilitating the model's ability to swiftly adapt to evolving trends.

(1) Brown's Linear Exponential Smoothing (B-DES) Method [5][11][15][21]

Exponential smoothing with a trend operates similarly to simple smoothing, with the distinction that two components require updating each period: the level and the trend. The level represents a smoothed estimation of the data value at the period's conclusion, while the trend signifies a smoothed estimate of the average growth by the period's end. Brown's linear exponential smoothing, also known as Brown's double exponential smoothing, is commonly applied to data exhibiting a linear trend. This method is utilized when the data displays a trend and aims to establish a linear trend. Consequently, Brown's exponential smoothing model is well-suited for modelling time series with a trend but lacking seasonality. In Brown's double exponential smoothing method, a single parameter denoted by α, whose value lies between 0 and 1, is employed. This parameter dictates the exponential decrease in the observed value (actual value) in previous periods. The equation for Double Exponential Smoothing Using Brown's method, with the m-period-ahead forecast, is provided as follows:

$$\mathrm{Z}_{\mathrm{t+m}} = \hat{\mathrm{a}} + \hat{\mathrm{b}}(\mathrm{m}) \qquad (2)$$

This is just a simple linear regression model.

Where:

$\mathrm{Z}_{\mathrm{t+m}}$: denotes the forecast ahead by (m) periods.

$(\hat{\mathrm{a}}.\hat{\mathrm{b}})$: represents parameters that are yet to be determined.

The process for determining the forecast ahead by m periods involves the following steps

Step 1 involves determining the coefficients for the linear trend, which proceeds as outlined below:

$$\hat{\mathrm{a}}_{\mathrm{t}} = 2(\mathrm{S}_{\mathrm{t}}^{1}) - (\mathrm{S}_{\mathrm{t}}^{2}) \qquad (3)$$

Where $(\mathrm{S}_{\mathrm{t}}^{1})$ is the single -Smoothing Measurement and $(\mathrm{S}_{\mathrm{t}}^{2})$ is the double-Smoothing Measurement. Then,

$$\hat{\mathrm{b}}_{\mathrm{t}} = \frac{\propto}{1-\propto}\,(\mathrm{S}_{\mathrm{t}}^{1} - \mathrm{S}_{\mathrm{t}}^{2}) \qquad (4)$$

Here, α represents the coefficient used in single exponential smoothing

$$\mathrm{S}_{\mathrm{t}}^{1} = \propto \mathrm{X}_{\mathrm{t}} + (1-\propto)\mathrm{S}_{\mathrm{t-1}}^{1} \qquad (5)$$

$$\mathrm{S}_{\mathrm{t}}^{2} = \propto \mathrm{S}_{\mathrm{t}}^{1} + (1-\propto)\mathrm{S}_{\mathrm{t-1}}^{2} \qquad (6)$$

It's important to note that in period (t = 1), the values of $(\mathrm{S}_{1}^{1} = \mathrm{S}_{1}^{2} = \mathrm{X}_{1})$

(2) Parameter Optimization of (B-DES) Method [13][20]

Parameter optimization was conducted using the golden section method to minimize the Mean Absolute Percentage Error (MAPE). This MAPE was derived from the forecast generated by Brown's method and was compared against the actual values. The optimization of the DES Brown's parameters (α) was accomplished utilizing the golden section method.

(3) Holt's Linear Exponential Smoothing (H-DES) Method [15][[20][21][23]

Holt (1957) expanded upon simple exponential smoothing to enable the forecasting of data exhibiting a trend. This approach incorporates a forecast equation along with two smoothing equations, one for the level and another for the trend:

$\hat{Z}_{t+m} = L_t + m\, b_t$ Forecast Equation (7)

$L_t = \propto Z_t + (1-\propto)(L_{t-1} + b_{t-1})$ Level Equation (8)

$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1}$ Trend Equation (9)

Where:

L_t: represents an estimation of the series' level at time t

b_t: represents an estimation of the trend (slope) of the series at time t..

∝: signifies the smoothing constant applied to the data, with a constraint of $0 < \propto < 1$.

β : signifies the smoothing constant applied to the trend estimation, with a constraint of $0 < \beta < 1$.

m: denotes the number of periods ahead to forecast.

$\hat{Z}_{t+m}$: Double forecast value of period(t+m)

Note: Initialization Level $L_1 = Z_1$ and Trend : $b_1 = \frac{(Z_2 - Z_1)}{(b_2 - b_1)}$ or $\frac{(Z_4 - Z_1)}{(b_4 - b_1)}$

(4) Parameter Optimization of Holt's (H-DES) Method [13][20]

Parameter optimization was carried out utilizing the golden section method to reduce the Mean Absolute Percentage Error (MAPE). This MAPE was calculated from the forecast generated by Holt's method and was compared with the actual values. The optimization of the parameters ($\propto$ and β) for DES Holt was conducted using a modified version of the golden section method.

4. Measures of Forecasting Accuracy [17][20]

Forecasting accuracy is crucial in selecting among various alternatives. Accuracy, in this context, pertains to forecasting error, which signifies the difference between the actual value and the forecasted value for a specific period. In this research, the determinant of forecasting error is the Mean Absolute Percentage Error (MAPE). MAPE is a measure that indicates the percentage of the average absolute error observed. This measure is represented by the following equation:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{z_t}\right| * 100 = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{z_t - \hat{z}_t}{z_t}\right| * 100 \qquad (10)$$

Where:

z_t: Actual demand for time period t $\qquad$ $\hat{z}_t$: Forecast demand for time period t

n: Specified number of time period $\qquad$ e_t: $z_t - \hat{z}_t$

5. Application

A. Introduction:

In this study, we employed time series data on the population density of Iraq spanning from the years 2000 to 2023. This dataset was sourced from the website (Earthly data-Iraq population density).https://database.earth/population/iraq/density). In this section, we utilized the two models discussed earlier to analyse the time series data on population density. Specifically, we applied the Single Exponential Smoothing (SES) model and the Double Exponential Smoothing (DES) model, including variants proposed by Brown and Holt, for forecasting the population density of Iraq over a period of 24 years, from 2000 to 2023.

B. Variable of this Study

The dataset employed for both Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) consists of population density records spanning from 2000 to 2023. This data is accessible in Table 1.

Table (1): population density of Iraq - Data from 2000 - 2023

Year	Population Density (people/km²)	Year	Population Density (people/km²)	Year	Population Density (people/km²)
2000	56.7318	2008	67.3036	2016	89.1395
2001	58.5672	2009	69.7698	2017	91.2661
2002	60.4783	2010	72.0176	2018	93.4994
2003	62.3522	2011	74.5818	2019	95.7402
2004	64.1722	2012	78.0057	2020	98.0287
2005	66.1065	2013	81.7312	2021	100.2782
2006	66.5831	2014	84.6444	2022	102.4954
2007	66.0194	2015	86.9739	2023	104.8183

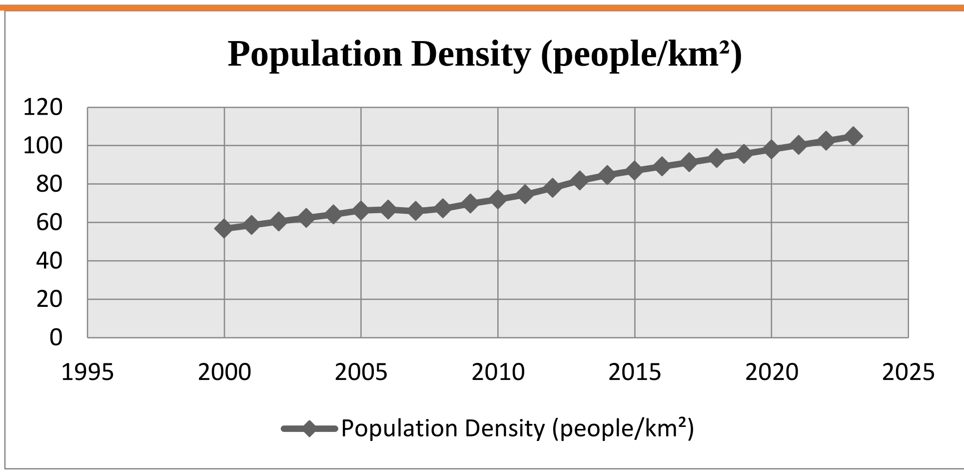

Fig.(1): Plot the data population density of Iraq from (24) years

According to the visualization provided in Figure 1 depicting the population density of Iraq, there appears to be a consistent trend observed from the year 2000 through to 2023.

C. Testing for stationary using the Dickey-Fuller Test:

The following presumptions guide the test's execution:

H0 :The unit root is present and is non-stationary. vs H1:The unit root is not exist and is stationary.

Table (2): Present Dickey-Fuller Test for stationary

Time series variable	T-Statistics	P-Value
Y= population density	1.181900	0.9966

From the table, we notice that the p-value of the test is (0.9966) and is greater than the level of significance ($\propto$=0.05), meaning we accept the null hypothesis. We say there exists a unit root in the time series, and it is non-stationary. We take the first difference for the purpose of obtaining stationary, then we test again to obtain stationary.

Table (3): Present Dickey-Fuller Test for stationary

Time series variable	T-Statistics	P-Value
Y= population density	-3.422326	0.0258

From the table, we notice that the p-value of the test is (0.0258) and is less than the level of significance ($\propto$=0.05), meaning we accept alternative hypotheses, which means the time series is stationary.

D. Results of Single Exponential Smoothing (SES) Method

(1) Applied Single Exponential Smoothing (SES) Method

The SES technique stems from simple moving averages but takes a singular approach in this scenario, specifically employing the one-parameter linear exponential smoothing derived from single exponential smoothing. Various test scenarios are then implemented with randomly assigned parameter values. This method involves testing across different levels of α, ranging from 0.1 to 0.9. The results of the Single Exponential Smoothing method's estimation are displayed in Table 4. According to the findings in Table 4, the minimum MAPE value is attained at α = 0.9. Thus, setting α to 0.9 yields the parameter choice that minimizes forecasting errors within the Single Exponential Smoothing model, making it the optimal parameter selection..

Table (4): Smoothing Parameter Selection for (SES) Method

A	MAPE	α	MAPE	α	MAPE
0.1	12.7943	0.4	5.65669	0.7	3.55791
0.2	9.19753	0.5	4.73912	0.8	3.17094
0.3	7.06466	0.6	4.05789	0.9	2.85409

(2) Parameter Optimization Results for SES Method

Optimization of the parameter α in the Single Exponential Smoothing method was performed using the golden section technique, and the results are presented in Table 5. Through this optimization process, it was determined that α = 0.99 leads to the optimal MAPE value of 2.61394. Therefore, setting α to 0.99 indicates the effectiveness of the Single Exponential Smoothing approach for prediction purposes. The optimization procedure has successfully identified the optimal MAPE value.

Table (5): Smoothing Parameter optimization Selection for (SES) Method

α	MAPE	α	MAPE	α	MAPE	α	MAPE	α	MAPE
0.85	3.00503	0.88	2.91281	0.91	2.82552	0.94	2.74276	0.97	2.66417
0.86	2.97372	0.89	2.88319	0.92	2.79745	0.95	2.71612	0.98	2.63885
0.87	2.94298	0.90	2.85409	0.93	2.76987	0.96	2.68993	0.99	2.61394

E. Results of Double Exponential Smoothing(DES) Applied Brown's Method

(1) Application of (B-DES) Method

For DES Brown testing, smoothing parameters (α) were selected from 0.1 to 0.9, with MAPE calculation results presented in Table 6. The forecasting model with the smallest MAPE value was chosen. The minimum MAPE value occurred at α = 0.9, with the DES model yielding a MAPE value of 0.901308, representing the minimum error for forecasting. Thus, the suitable parameter for DES Brown is α = 0.9.

Table (6): Smoothing Parameter Selection for (B-DES) Method

α	MAPE	α	MAPE	α	MAPE
0.1	13.4426	0.4	2.06933	0.7	1.21118
0.2	5.73787	0.5	1.70649	0.8	1.03908
0.3	2.86351	0.6	1.41737	0.9	0.901308

(2) Parameter Optimization Results for (B-DES) Method

The optimization of DES Brown's parameter (α) was conducted using the golden section method, as displayed in Table 7. The optimization results indicate that α = 0.99 leads to the optimal MAPE value of 0.817392. This finding suggests that the DES Brown method is effective for prediction based on the obtained optimum MAPE value.

Table (7) Smoothing Parameter optimization Selection for (B-DES) Method

α	MAPE	α	MAPE	α	MAPE	α	MAPE	α	MAPE
0.85	0.967935	0.88	0.92758	0.91	0.888376	0.94	0.857999	0.97	0.834024
0.86	0.954364	0.89	0.914377	0.92	0.875585	0.95	0.850142	0.98	0.82577
0.87	0.94091	0.90	0.901308	0.93	0.866104	0.96	0.842149	0.99	0.817392

F. Results of Double Exponential Smoothing (DES) Applied Holt's Method

(1) Application of (H-DES) Method

In DES Holt testing, smoothing parameters (α, β) were selected systematically, ranging from 0.1 to 0.9 for both α and β, with MAPE calculation results provided in Table 8. From these trials, it was observed that the combination of α = 0.9 and β = 0.9 produced the smallest error, with a MAPE value of 0.609068. Thus, the suitable parameter for DES Holt is α = 0.9 and β = 0.9.

Table (8): MAPE value for (H-DES) Method

α \ β	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	2.69879	2.89558	2.93315	2.81472	2.74308	2.71564	2.70466	2.69005	2.64492
0.2	2.25752	2.16848	2.10268	2.11417	2.2005	2.25767	2.28926	2.30102	2.3135
0.3	1.70963	1.65685	1.75192	1.84112	1.88551	1.91236	1.89524	1.89673	1.88894
0.4	1.33685	1.39596	1.53158	1.57427	1.55614	1.53943	1.5048	1.4812	1.43055
0.5	1.10349	1.23811	1.32113	1.2978	1.26723	1.21705	1.17251	1.13281	1.08067
0.6	0.976413	1.08905	1.11761	1.08609	1.02754	0.972053	0.940777	0.916115	0.885154
0.7	0.880359	0.957214	0.970508	0.914056	0.848829	0.833977	0.815426	0.789589	0.754897
0.8	0.799164	0.840488	0.843208	0.796548	0.769097	0.751794	0.73008	0.703965	0.674638
0.9	0.725043	0.751002	0.755378	0.728192	0.708741	0.687208	0.665468	0.638269	0.609068

(2) Parameter Optimization Results for (H-DES) Method

The optimization of parameters (α and β) for DES Holt was executed using a modified golden section method, with the results presented in Table 9. The optimization process revealed optimum values of α = 0.99 and β = 0.99, resulting in a MAPE value of 0.550475. Therefore, it can be concluded that the DES Holt method is effective for prediction based on the obtained optimal MAPE value.

Table (9) Smoothing Parameters Optimization Selection for (H-DES) Method

MAPE								
β \ α	0.84	0.85	0.86	0.87	0.88	0.89	0.9	0.91
0.84	0.66495	0.658355	0.651858	0.645452	0.639127	0.632878	0.626696	0.620574
0.85	0.662028	0.655435	0.64894	0.642534	0.636209	0.629958	0.623772	0.617646
0.86	0.659093	0.652504	0.646011	0.639607	0.633282	0.627029	0.620841	0.614711
0.87	0.656148	0.649563	0.643074	0.636671	0.630347	0.624094	0.617903	0.611769
0.88	0.653194	0.646615	0.64013	0.63373	0.627407	0.621154	0.614961	0.608823
0.89	0.650235	0.643662	0.637181	0.630785	0.624464	0.61821	0.612015	0.605873
0.90	0.647272	0.640705	0.63423	0.627837	0.621518	0.615264	0.609068	0.602921
0.91	0.644306	0.637747	0.631277	0.624888	0.618571	0.612317	0.606119	0.599969
0.92	0.641339	0.634788	0.628325	0.62194	0.615625	0.609371	0.603171	0.597017
0.93	0.638374	0.631831	0.625374	0.618993	0.61268	0.606427	0.600225	0.594066
0.94	0.63541	0.628876	0.622425	0.616049	0.609739	0.603485	0.597281	0.591117
0.95	0.632451	0.625925	0.619481	0.613109	0.606801	0.600547	0.59434	0.588172
0.96	0.629496	0.622978	0.616541	0.610174	0.603867	0.597613	0.591403	0.586246
0.97	0.626547	0.620038	0.613608	0.607244	0.60094	0.594684	0.5885	0.585542
0.98	0.623605	0.617105	0.610681	0.604322	0.598018	0.591762	0.587849	0.584819
0.99	0.62067	0.61418	0.607761	0.601406	0.595103	0.590055	0.587182	0.584077
α	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99

β								
0.84	0.614507	0.608488	0.602511	0.596572	0.590666	0.58479	0.578939	0.573113
0.85	0.611573	0.605546	0.59956	0.59361	0.587692	0.581801	0.575936	0.570093
0.86	0.608631	0.602597	0.596601	0.590641	0.58471	0.578805	0.572924	0.567499
0.87	0.605684	0.599642	0.593637	0.587665	0.581722	0.575803	0.570243	0.5664
0.88	0.602732	0.596682	0.590668	0.584685	0.578729	0.572932	0.569199	0.565268
0.89	0.599776	0.593719	0.587695	0.581701	0.575732	0.571943	0.568123	0.564102
0.90	0.596819	0.590754	0.58472	0.578715	0.574626	0.570924	0.567016	0.562901
0.91	0.59386	0.587787	0.581744	0.577243	0.573664	0.569875	0.565876	0.561666
0.92	0.590902	0.58482	0.579787	0.576338	0.572674	0.568796	0.564703	0.560396
0.93	0.587945	0.582254	0.578938	0.575406	0.571656	0.567685	0.563496	0.55909
0.94	0.584989	0.58146	0.578065	0.574448	0.570608	0.566543	0.562255	0.557748
0.95	0.583898	0.580644	0.577167	0.573463	0.56953	0.565368	0.56098	0.556369
0.96	0.583138	0.579806	0.576244	0.572449	0.568422	0.564161	0.55967	0.554952
0.97	0.582358	0.578944	0.575294	0.571407	0.567282	0.56292	0.558324	0.553498
0.98	0.581557	0.578058	0.574318	0.570336	0.566111	0.561645	0.556941	0.552006
0.99	0.580734	0.577148	0.573315	0.569235	0.564907	0.560334	0.555522	0.550475

Table (10): Represents the accuracy of models

Criteria	SES	DES Brown's	DES Holt's	Conclusion
MAPE	2.61394	0.817392	0.550475	The DES Holt's is the accurate model

Forecast Summary

*Forecast model selected: Simple exponential smoothing with alpha = 0.99
*Forecast model selected: Brown's linear exp. smoothing with α = 0.99
*Forecast model selected: Holt's linear exp. smoothing with alpha = 0.99 and beta = 0.99

Table 10 illustrates that the DES Holt's method exhibits the smallest MAPE value when compared to DES Brown's and SES methods. These findings lead to the conclusion that the DES Holt's method stands as the most accurate model for predicting future population density in Iraq. Detailed forecasted values for the years 2024-2030 are provided in Table 11 and Fig. 2.

Table (11): The forecasted the population density in Iraq during the period (2024-2030)

Years	2024	2025	2026	2027	2028	2029	2030
Forecast	107.138	109.458	111.779	114.099	116.42	118.74	121.061

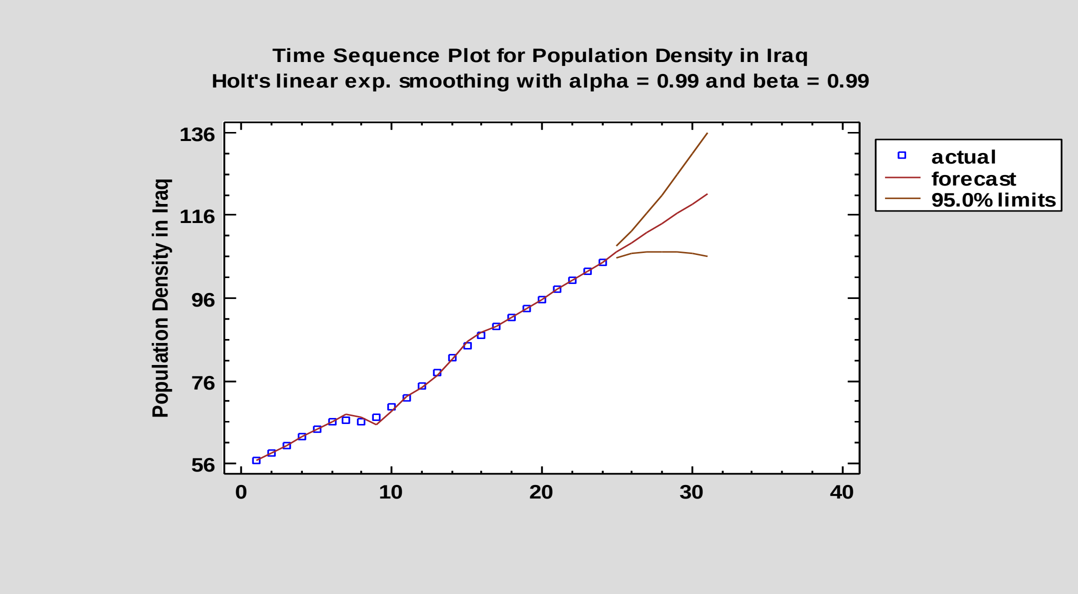

Fig.(2): The forecasted the population density in Iraq during the period (2024-2030) applied the DES Holt's

6. Discussion

The main objective of this study is to determine the most precise forecasting model for population density. Three distinct forecasting models were suggested and evaluated: the Single Exponential Smoothing (SES) model, along with the Double Exponential Smoothing (DES) models by Brown's and Holt's methodologies. These models were applied to forecast population density in Iraq spanning a duration of 24 years, from 2000 to 2023. The necessary data were sourced from the website (Earthly data-Iraq population density). (https://database.earth/population/iraq/density). The selection of the most precise forecasting model relies on identifying the model with the lowest MAPE value. Through the optimization process, the SES method determined an optimal α value of 0.99, resulting in a MAPE of 2.61394. Similarly, optimization of the α parameter in the DES Brown's method yielded an optimal α=0.99, with an associated MAPE peaking at 0.817392. Furthermore, optimization outcomes from the DES Holt's method, incorporating optimal values of α=0.99 and β=0.99, demonstrated the lowest MAPE value at 0.550475. Hence, it is concluded that the DES Holt's method stands as the most accurate model, exhibiting the lowest MAPE value compared to alternative forecasting methods.

7. Conclusion and Recommendation

In this research, a comparative analysis was conducted to assess the forecasting performances of the SES and DES models, including those proposed by Brown and Holt, for population density in Iraq. This methodology enabled the prediction of future population density values in Iraq, utilizing data spanning a period of 24 years. Additionally, optimization results from the SES model revealed an optimal α=0.99, resulting in an associated MAPE of 2.61394. Optimization of the α parameter in the DES Brown's method identified an optimal value of α=0.99, along with an associated MAPE and MSE of 0.817392. Furthermore, optimization procedures for the α and β parameters within the DES Holt's method led to the determination of an optimal value denoted as α=0.99 and β=0.99, resulting in a MAPE of 0.550475. The selection of the accurate forecasting model is based on the smallest MAPE value. Consequently, it can be concluded that DES Holt's method is the most appropriate approach for the population density data in Iraq, as it produced the lowest MSE value of 0.550475. Utilizing the Holt's method, population density in Iraq was forecasted from 2024 to 2030, indicating an anticipated increase during this period. Moreover, it is recommended that future studies incorporate additional statistical methodologies, such as neural networks or GM(1,1), to achieve more precise and reliable population density forecasts.

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